



Energy market uncertainty and the impact on the crude oil prices

Bing Xu^{a,1,*}, Rong Fu^b, Chi Keung Marco Lau^{c,*}

^a Edinburg Business School, Heriot-Watt University, Edinburgh, EH14 4AS, UK

^b Rokos Capital Management, London, W1S 2ET, UK

^c Teesside University Business School, Teesside University, Middlesbrough, TS1 3BX, UK

ARTICLE INFO

JEL classification:

C30
E30
F00

Keywords:

Oil prices
Uncertainty
Alternative energy demand
Carbon neutrality
Bayesian VAR
Quantile VAR

ABSTRACT

Our paper proposes a novel measure of global energy market uncertainty and studies its impact on oil prices. The current literature primarily relies on a single or small number of observable variables, or general macroeconomic uncertainty (JLN) and economic policy uncertainty (EPU) indices to reflect energy market uncertainty. Using a Factor Augmented Vector Autoregression model (FAVAR), we construct time-varying global energy market uncertainty in a data-rich environment. Our estimates show variations from JLN and EPU proxies. The results reveal that real oil prices respond strongly to our proposed aggregate energy market uncertainty shocks. We also find heterogeneous responses to different types and magnitudes of uncertainty shocks. The real price of oil is affected the most under unexpected strong demand for alternative energy sources scenario.

1. Introduction

There is growing evidence linking climate change with escalated frequency and/or magnitude of extreme weather-related events (e.g., heatwaves, hurricanes, floods and storms), that constitute substantial risks to firms and society at large (IPCC, 2018). The Paris Agreement is a legally binding global climate change pact signed in 2016. All 196 nations agreed to set Nationally Determined Contributions (NDCs) to minimize their emissions and contain global warming to the 1.5–2 °C above pre-industrial levels. The effectiveness of the agreement depends on the extent to which the NDCs are fully implemented and there are enormous challenges to fulfil countries' pledges to a pathway consistent with carbon neutrality. One of the major challenges is the volatility of the oil price, streaming from global shocks, including the COVID-19 pandemics, economic crises, and climate-related disasters (Dechezlepretre et al., 2020). To be more specific, a highly volatile oil market can affect the investment in low-carbon and energy efficiency technologies, coupled with profitability uncertainty as the economic crisis hammers fuel demand. Therefore, uncertainty regarding oil price movement can have a negative impact on the success of reaching carbon neutrality targets. Furthermore, central banks take oil price volatility into

consideration when constructing their monetary policies in stimulating the economy during the crisis period (e.g., COVID-19 pandemic crisis). Therefore, it is not surprising to see extensive literature on modelling the key determinants of the real price of oil.

Oil supply and demand are believed to have played important roles in affecting oil prices (e.g., Hamilton, 2003; Kilian, 2009). One factor that has received less attention is the impact of uncertainty raised from the global energy market on oil prices (Van Robays, 2016). Given that uncertainty is not directly observable, most studies have depended on indicators or proxies of uncertainty based on a single or small number of variables, such as conditional volatility, implied, realized, or stochastic volatility of oil prices, stock market indices and commodity indices (e.g., Van Robays, 2016; Jo, 2014). However, Jurado et al. (2015) argue that uncertainty representing conditional volatility of a disturbance cannot be forecast in terms of economic agents, and failure to remove forecastable components can incorrectly classify forecastable variations as uncertainty. Several uncertainty proxies have been developed to overcome the above-mentioned drawbacks, such as extract macroeconomic uncertainty (JLN) from 132 macroeconomic variables, and use of newspaper coverage frequency to construct economic policy uncertainty (EPU) indicator. Yet, there is a lack of an energy market specific

* Corresponding authors.

E-mail addresses: b.xu@hw.ac.uk (B. Xu), lotusfurong123@gmail.com (R. Fu), c.lau@tees.ac.uk (C.K.M. Lau).

¹ I wish to acknowledge funding of the "Low carbon jet fuel through integration of novel technologies for co-valorisation of CO₂ and biomass" project by the Engineering and Physical Sciences Research Council (EPSRC) (EP/N009924/1).

<https://doi.org/10.1016/j.jenvman.2021.113403>

Received 5 March 2021; Received in revised form 22 July 2021; Accepted 26 July 2021

Available online 6 August 2021

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uncertainty proxy that reflects fluctuations in the global energy market.

In this paper, we propose a different measure of global energy market specific uncertainty. Following [Jurado et al. \(2015\)](#) approach, we first apply a factor augmented vector autoregression (FVAR) model to forecast time-varying energy market uncertainty by focusing on the variance of the forecast errors. Next, we estimate the stochastic volatility parameters from forecasting models' least square residuals based on the Markov Chain Monte Carlo (MCMC) approach. As far as the authors are aware, we are the first to construct time-varying global energy market uncertainty in a data-rich environment using this method. Our energy market uncertainty indicator is not reliant on a specific theoretical model, it measures the common fluctuations in uncertainty across 216 series, ranging from energy prices, conventional and alternative energy demand, fossil-fuel and alternative energy supply, inventories, key macroeconomic and financial variables. In addition to obtaining the aggregate energy market uncertainty indicator, we account for heterogeneity in the energy market by tracing seven factor-specific energy market uncertainties.

While the focus of this paper is to construct energy market uncertainty proxies, another contribution is to capture the impulse responses of oil prices to shocks in uncertainty measures using both Bayesian Structural VAR (B-SVAR) and Quantile SVAR (Q-SVAR) models. Our results highlight the ability of our proposed energy market uncertainty index to capture uncertain components in the energy market. While oil prices respond negatively to energy market uncertainty in general, we also show that sectoral uncertainty factors react differently to oil prices. For example, shocks raised from macroeconomic and financial factors exhibit a strong and immediate effect on the real price of oil, whereas the impacts of alternative energy demand shocks are delayed. However, energy demand shocks, energy supply shocks and inventory shocks have negligible effects on the real price of oil. Furthermore, we simulate low, medium, and high alternative energy demand uncertainty scenarios to examine the implications of the Paris Agreement on the energy market. Our results reveal that the oil price responds differently to unexpected, strong demand from renewable energy sources, ranging from a minor 0.04 drop in standardized price in a low uncertainty scenario to a significant 0.35 decrease under high uncertainty case.

The remainder of the paper is organized as follows. Section 2 summarizes the prior literature. Sections 3 and 4 report our methodologies and the data used in this paper. We discuss our empirical findings in section 5, and provide a concluding remarks in section 6.

2. Literature review

Our paper relates to the literature on investigating the relationship between carbon neutrality targets and economics growth or environmental performance. [Fang et al. \(2019\)](#) for example, examine the determinants of carbon dioxide (CO₂) emissions, and find significant evidence that trade openness and export upgrade does not help to achieve carbon neutrality targets. However, the impact of export quality is negatively related to CO₂ emissions for the Chinese economy ([Gozgor and Can, 2017](#)). There is also significant evidence showing that higher consumption on renewable energy improves countries' environmental quality and sustainability, while the use of non-renewable energy leads to degradation of the environment (e.g., [Khan et al., 2020a,b,c](#); [Nathaniel and Khan, 2020](#); [Azam et al., 2021](#)). Several authors use firm-level data and show that the firms' environmental performance can be improved by adopting green practices on the supply chain management (e.g., [Khan et al., 2020c](#)).

Furthermore, [Doukas et al. \(2018\)](#) propose an interactive paradigm to address the challenges related to the success of carbon neutrality targets. The authors introduce an integrated assessment framework which consists of three main pillars to support the design of effective climate policy, emphasizing the use of diverse modelling ensembles. They also suggest including the involvement of human factors in the model-driven policy prescriptions via decision support systems. [Santos](#)

(2017) pinpoints two biggest obstacles for achieving carbon neutrality targets consist of the global deal and the high relative cost of clean technologies. The first obstacle has been addressed by the Paris Agreement, and the latter, as suggested by the author, could potentially be solved via the implementation of environmental taxes and subsidies. Note that environmental policies can affect oil price volatility and, subsequently, affect investment on clean energy technology in return. Furthermore, the speed and scale of transition to net zero and adoption of green technologies is greatly associated to oil price movements ([Dechezlepretre et al., 2020](#)). Therefore, researchers have expended considerable effort on understanding the key determinants of oil prices, as many decision makers deem fluctuations to be key to investment, consumption and production decisions, risk management, and policy formulations.

[Table 1](#) summarizes the main drivers of price fluctuations in the literature. Initially, oil price fluctuations were considered primarily to be affected by unforeseen supply shocks raised from conflicts and/or cuts in oil producing countries (e.g., [Hamilton, 2003](#)). Subsequent research has highlighted that changes to demand for worldwide industrial commodities and unexpected preventative purchases have played a critical role in influencing the price of oil. For example, [Kilian \(2009\)](#) untangles the impacts of demand and supply side shocks that underpin the development of oil prices, and many authors confirm and extend the results of [Kilian \(2009\)](#) (e.g., [Abhyankar et al., 2013](#); [Kang and Ratti, 2013](#)). The dramatic fluctuations in oil prices following the 2007–2008 Global Financial Crisis have inspired researchers to explore further possible determinants. [Sackin and Xiong \(2015\)](#) point out that during periods of extreme uncertainty, it is tricky for producers and consumers to simultaneously observe whether the current level of the oil price is too high or too low with respect to fundamentals for formulating their decisions in investments or consumption. [Byrne et al. \(2019\)](#) incorporate the role of expectations proxied by the sentiment indicators and find that the expectations of business leaders' have a substantial and positive effect on the oil market. The reader is referred to [Degiannakis et al. \(2018\)](#) for a detailed review on oil prices.

One strand of literature focuses on examining the effect of uncertainty on oil prices and finds mixed results. This is sensible as rising uncertainty increases the value of waiting and discourages investment. However, delaying investment can allow competitors to seize the opportunity to grow ([Kulatilaka and Perotti, 1998](#)). [Antonakakis et al. \(2014\)](#), for instance, study the extent to which the price of oil responds to economic policy uncertainty, and find that a higher level of EPU leads to a significant decline in oil prices up to three months. However, [Aloui et al. \(2016\)](#) highlight that an increase in EPU can generate either positive or negative effects on oil returns depending on the overall economic situation. [Van Robays \(2016\)](#) uses global industrial production volatility as a proxy for macroeconomic uncertainty, and suggests that the sensitivity of oil prices to oil demand and supply shock increases along with the severity of uncertainty. In addition, [Bekiros et al. \(2015\)](#) find that EPU enhances the out-of-sample predictability of oil price changes.

Table 1
Summary of oil prices determinant studies.

Study	Methodology	Key Determinants
Hamilton (2003)	Parametric nonlinear models	Oil supply shock
Kilian (2009)	Structural VAR (SVAR) model	Demand shocks
Antonakakis et al. (2014)	SVAR model	Economic policy Uncertainty (EPU)
Bekiros et al. (2015)	Time-varying parameters (TVP) - VAR Approach	EPU
Aloui et al. (2016)	Time-varying Copula Approach	EPU
Van Robays (2016)	Threshold VAR Model	Macroeconomic Uncertainty
Byrne et al. (2019)	Bayesian VAR TVP-VAR	Oil fundamentals; Expectations shocks

Several authors scrutinize how different macroeconomic activities (e.g., GDP, investments, consumption, and industrial productions) respond to energy market uncertainty. For example, [Elder and Serletis \(2010\)](#) find US investments, consumption and outputs respond negatively to oil price uncertainty measured by the conditional variance of oil prices. [Jo \(2014\)](#) proxies oil price uncertainty via stochastic oil price volatility and finds that higher levels of uncertainty depress world industrial production.

In this study, different from the previous literature, our investigation focuses on proposing a new measure of global energy market uncertainty and studies its impact on the oil market.

3. Methodology

In this section, we first describe our econometric framework for constructing the specific global energy market uncertainty. Specially, we first use the FAVAR to forecast each of the energy-related variables we consider and treat the aggregate forecast error as the energy market uncertainty. We then outline the B-SVAR and Q-SVAR models to ascertain how changes in fundamentals and uncertainty influence oil prices.

3.1. Construction of energy uncertainty

Following [Jurado et al. \(2015\)](#), we construct our energy market uncertainty index. Assume $\mathbf{X}_t = (X_{1t}, \dots, X_{N_t})'$ are the predictors available at time t , where \mathbf{X}_t has been transformed to be stationary. We presume that \mathbf{X}_{it} has an approximate factor structure:

$$X_{it} = \Lambda_i^F \mathbf{F}_t + e_{it}^X \quad (1)$$

where \mathbf{F}_t is the latent common factors extracted using principal component analysis, Λ_i^F is the corresponding factor loadings, and e_{it}^X is a vector of unobserved errors.

Let y_{it} denote an energy-related series we consider, and its value is estimated from a factor augmented model:

$$y_{i,t+1} = \sum_{i=1}^p y_{j,t} + \sum_{i=1}^q \hat{\mathbf{F}}_t + \sum_{i=1}^r \hat{\mathbf{W}}_t + v_{it+1}^y \quad (2)$$

where $\hat{\mathbf{F}}_t$ is the consistent estimator of \mathbf{F}_t and $\hat{\mathbf{W}}_t$ contains r_W additional predictors. Importantly, we assume time-varying volatility $\sigma_{j,t+1}^y$, $\sigma_{q,t+1}^F$, and $\sigma_{p,t+1}^W$ for the predictor errors of $y_{j,t+1}$, factor $F_{q,t+1}$, and additional predictor $W_{p,t+1}$, respectively. This characteristic constructs time-varying uncertainty in $y_{j,t}$.

We can rewrite the above system in a FAVAR representation. Let $\mathbf{M}_t \equiv (\hat{\mathbf{F}}_t', \mathbf{W}_t')'$ be a vector that collects the r_F estimated factors and r_W additional predictors, and assume $\mathcal{M}_t \equiv (\mathbf{M}_t', \dots, \mathbf{M}_{t-q+1}')$, $\mathbf{Y}_{jt} \equiv (y_{jt}, \dots, y_{jt-q+1})'$. Therefore, forecasts can be obtained from the following FAVAR model, stacked in a companion form:

$$\begin{pmatrix} \mathcal{M}_t \\ \mathbf{Y}_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^{\mathcal{M}} & 0 \\ \Lambda_j^Y & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{M}_{t-1} \\ \mathbf{Y}_{j,t-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^{\mathcal{M}} \\ \mathcal{V}_{jt}^Y \end{pmatrix} \quad (3)$$

$$\mathcal{V}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{V}_{j,t-1} + \mathcal{V}_{jt}^{\mathcal{Y}}$$

where Λ_j^Y and Φ_j^Y are the coefficients in the lag polynomials in equation (2), $\Phi^{\mathcal{M}}$ contains the autoregressive coefficients of \mathcal{M}_t .

Therefore, $\mathcal{U}_{it}^y(h)$, the expected forecast uncertainty of series $y_{j,t+h}$ at time t , can be shown as:

$$\mathcal{U}_{it}^y(h) = \sqrt{1_j' E_t[(\mathcal{V}_{j,t+h} - E_t \mathcal{V}_{j,t+h})(\mathcal{V}_{j,t+h} - E_t \mathcal{V}_{j,t+h})'] 1_j} \quad (4)$$

with 1_j being the selection vector.

To estimate energy uncertainty, we construct the weighted average

of individual uncertainty estimates:

$$\sum_{j=1}^{N_y} \mathbf{w}_M \mathcal{U}_{i,t}^y(h) \quad (5)$$

and we assume equal weight for each of the individual uncertainty index: $w_j = 1/N_y$.

3.2. Time-varying uncertainty

Next, we introduce predictors \mathbf{M} and y_j 's time-varying stochastic volatility and analyze how they contribute to the time-varying uncertainty. First, we assume that the factors \mathbf{F}_t are serially correlated and follow a univariate AR(1) process, the argument for \mathbf{W}_t is similar:

$$\mathbf{F}_t = \Phi^F \mathbf{F}_{t-1} + \mathbf{v}_t^F \quad (6)$$

If \mathbf{v}_t^F has constant variance $(\sigma_t^F)^2$, the forecast error variance increases with the forecast horizon h but is constant over time. Thus, we permit the shocks to \mathbf{F}_t to have time-varying stochastic volatility that is independent to y_j 's errors i.e., $\mathbf{v}_t^F = \sigma_t^F \varepsilon_t^F$, where log volatility can be represented as:

$$\log(\sigma_t^F)^2 = \alpha^F + \lambda^F \log(\sigma_{t-1}^F)^2 + \tau^F \eta_t^F \varepsilon_t^F \cdot \widetilde{d} \cdot N(0, 1) \quad (7)$$

and the log volatility has a level-effect α^F , a scale effect τ^F and a persistence effect λ^F . The stochastic volatility parameters α^F , τ^F and λ^F can be obtained using the residuals of the forecasting model using the MCMC approach. We use R package STOCHVOL to carry out the analysis. The model also implies:

$$E_t(\sigma_{t+h}^F) = \exp \left[\alpha^F \sum_{s=0}^{h-1} (\lambda^F)^s + \frac{(\tau^F)^2}{2} \sum_{s=0}^{h-1} (\lambda^F)^{2s} + (\lambda^F)^h \log(\sigma_t^F)^2 \right] \quad (8)$$

As the behavior of ε_t^F is by assumption iid, $E_t(\mathbf{v}_{t+h}^F)^2 = E_t(\sigma_{t+h}^F)^2$. The $h > 1$ forecast error variance for F can be computed as:

$$\Omega_t^F(h) = (\Phi^F)^h \Omega_t^F(1) (\Phi^F)^{h-1} + E_t(\mathbf{v}_{t+h}^F \mathbf{v}_{t+h}^{F'}) \quad (9)$$

with $\Omega_t^F(1) = E_t(\mathbf{v}_{t+1}^F \mathbf{v}_{t+1}^{F'})$.

3.3. Bayesian Structural VAR model

Our paper follows the SVAR model of the oil prices put forward by [Kilian \(2009\)](#). The basic SVAR model can be expressed as follows:

$$A_0 X_t = \sum_{i=1}^p \Gamma_i X_{t-i} + u_t, t = p+1, \dots, T \quad (10)$$

where X_t consists of a vector of endogenous variables: the changes of world oil production (ΔS_t), global real economic activity proxy (D_t), energy market uncertainty we constructed (U_t), and the real price of oil (O_t). Denote Γ_i as a 4×4 matrix of coefficients, A_0 as a matrix of X_t 's concurrent coefficients, and u_t are the structural shocks. The lag length is $p = 4$. With respect to identification, we place a recursive structure on the contemporaneous terms to orthogonalize the shocks. Particularly, the reduced-form errors ε_t are decomposed into the structural shocks u_t as follows:

$$\varepsilon_t \equiv \begin{pmatrix} \varepsilon_t^{\Delta S_t} \\ \varepsilon_t^{D_t} \\ \varepsilon_t^{U_t} \\ \varepsilon_t^{O_t} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{pmatrix} u_t^{Supply} \\ u_t^{Demand} \\ u_t^{Uncer} \\ u_t^{Res} \end{pmatrix} \quad (11)$$

It is clear from equation [11] that the oil price is influenced by four structural shocks. Firstly, u_t^{Supply} implies an unforeseen change in the world oil supply. Rather than being caused by changes in the

macroeconomy, these shifts are usually caused by exogenous production disruptions resulting from geo-political issues or alternations to production quotas from OPEC nations. Secondly, u_t^{demand} shows shifts in global demand for industrial commodities includes oil which is linked with variation in the global outlooks. Next, u_t^{uncer} reveals the variations of uncertainty about future energy market conditions. Uncertainty may vary in terms of elevated risk or uncertainty in global energy markets. Finally, u_t^{res} reflects the residual shock that is unassociated with oil market shocks.

Next, we apply the independent Normal-Wishart prior to estimating our B-SVAR model. The MCMC method is then used to estimate the conditional posterior distributions and obtain the prior with a training sample (Primiceri, 2005).

3.4. Quantile structural VAR model

Note that the SVAR model and the impulse response functions (IRFs) described in Section 3.3 cannot simulate and control the evolution of the variable of interest. Our paper also contributes to the literature by introducing the quantile SVAR framework to examine the impact of alternative energy demand uncertainty on real oil prices under different scenarios.

In this section, we simulate three scenarios on the response of oil price to uncertainties of alternative energy demand. The first assumes the magnitude of uncertainty regarding alternative energy demand is small; the second assumes a medium degree of alternative energy demand uncertainty; the last scenario assumes a strong unexpected demand from alternative energy sources. Following Caraianni et al. (2021), simulations of the above scenarios are carried out using a Q-SVAR model, where quantiles-based IRFs of oil price following a shock to the alternative energy demand uncertainty can be estimated. We investigate such IRFs by imposing different quantiles of alternative energy demand uncertainty.

The reduced form of VAR for γ th quantile can be specified as following:

$$X_t = c(\gamma) + \sum_{i=1}^p (\gamma) X_{t-i} + u_t(\gamma), t = p+1, \dots, T \quad (12)$$

where $c(\gamma)$ represents an intercept vector with quantiles γ ; $B_i(\gamma)$ is lagged coefficient matrix, and $u_t(\gamma)$ is the error terms with quantiles γ . We examine the effect of alternative energy demand uncertainty on real oil price, holding quantiles of other variables at its middle distribution (i.e. $\gamma = 0.5$). The innovation terms $u_t(\gamma)$ follow the restrictions as follows:

$$Q_\gamma(u_t(\gamma) | Y_{t-1}, \dots, Y_{t-p}) = 0 \quad (13)$$

At quantiles γ , the population responses of X_t can be specified as:

$$Q_\gamma(u_t(\gamma) | X_{t-1}, \dots, X_{t-p}) = c(\gamma) + \sum_{i=1}^p B_i(\gamma) X_{t-i} \quad (14)$$

We estimate each quantile γ by using Cecchetti and Li (2008)'s quantile regression approach. Next, we estimate the dynamic structural shock of how uncertainty influences the real price of oil. The confidence interval at the 95 % level is calculated by the 'bootstrapping' method, with 5000 replications. We use the re-sampling method from the estimated residuals. The IRF is plotted to investigate the impact of a one standard deviation rise of alternative energy demand uncertainty's innovation at t on oil price at s -months ahead. We position the IRFs on $\gamma = 0.2$ to reflect a low level of uncertainty, $\gamma = 0.5$ for medium uncertainty, and $\gamma = 0.8$ represents extremely high levels of uncertainty.

4. Data

To construct an energy uncertainty index capable of accommodating information from all possible areas that could affect and disturb the energy market, we obtained a large set of 216 monthly time series data from the Energy Information Administration (EIA) and DataStream for the period from 1988:M6 to 2017:M8. Our 216 variables are divided into

seven main categories depending on the nature of the series; namely, energy prices, conventional energy demand, alternative energy demand, energy supply, alternative energy demand, energy supply, inventory, macroeconomic and financial factors. Detailed information on our data is available upon request.

In addition to the energy market uncertainty index, we include three extra variables in our Bayesian and Quantile VAR analysis to examine the impact of uncertainty originating from the global energy market. First, the percentage change of oil production is used to represent shifts in global oil supply (ΔS_t). The world crude oil production data are extracted from the EIA. Furthermore, we use 's global economic activity proxy (D_t) based on the global dry cargo ocean shipping freight rates to capture the global demand for industrial commodities. Last, we employ the real price of West Texas Intermediate (WTI) from Datastream to capture the crude oil price (O_t) in our VAR model. Note that we adjusted monthly WTI crude oil prices to the US inflation rate, and we follow Kilian and Murphy (2012) to standardize the variables in logs deviations from their trend and mean.

5. Empirical results

In this section, we present our main results on the estimates of energy market uncertainty and the determinants of oil prices. First, we show our estimates of overall energy market uncertainty and compare them with other existing uncertainty indicators. Next, we decompose our aggregate energy market uncertainty into seven sectoral-specific uncertainties. Importantly, we use both B-SVAR and Q-SVAR models to inspect the responses of oil prices to our uncertainty measures' innovations.

5.1. Estimates of energy market uncertainty

The FAVAR model allows us to predict time-varying energy market uncertainty to capture the aggregate uncertainty, and track the development in different sectors for 1, 3 and 12 months ahead. Fig. 1 presents the behavior and dynamics of aggregate energy uncertainty $U_t^E(h)$ from 1986 to 2017. For each series, we have a corresponding dashed line indicating its standard deviations above the average value. Our results reveal that energy market uncertainty has been significantly affected by various events such as global outlooks, political instability and turmoil in oil producing nations. For the 1-month and 3-months forecasting horizons, we find significant levels of energy market uncertainty during the following three periods: 1) 1988 oil price rises; 2) the Gulf War in 1991; and 3) the Great Recession of 2007–2008. For the longer forecast horizon $h = 12$, there are two extra periods that exceed 1.65 standard deviation above its mean: 1998 and 2015. This is sensible as the level of uncertainty is likely to be higher with longer forecasting horizons as economic agents are more uncertain about the energy market into the more distant future.

Next, we compare our energy uncertainty index with two popular uncertainty indices including Baker et al. (2016)'s EPU, and the JLN macroeconomic uncertainty index from Jurado et al. (2015). Fig. 2 compares three uncertainty indicators over time and Table 2 reports the correlation between them. Our energy uncertainty measure is positively related to the EPU and JLN, with correlation coefficients of 0.06 and 0.49 respectively. Note that the correlation between energy uncertainty and macroeconomic uncertainty is higher because we also include some macroeconomic variables to construct our energy uncertainty index. The three spikes of macroeconomic uncertainty (i.e., 1991, 2001 and 2007–2009) generally correspond to economic recessions. Besides incorporating information from the whole economy, energy uncertainty captures fluctuations from the global energy market such as the Iran-Iraq war until 1988, reduced demand due to the Asia crisis from 1997, the global oil glut from 2014 to 2015 due to the US oil shale revolution. All these imply that the energy market uncertainty index constructed in this paper captures additional insights into uncertain

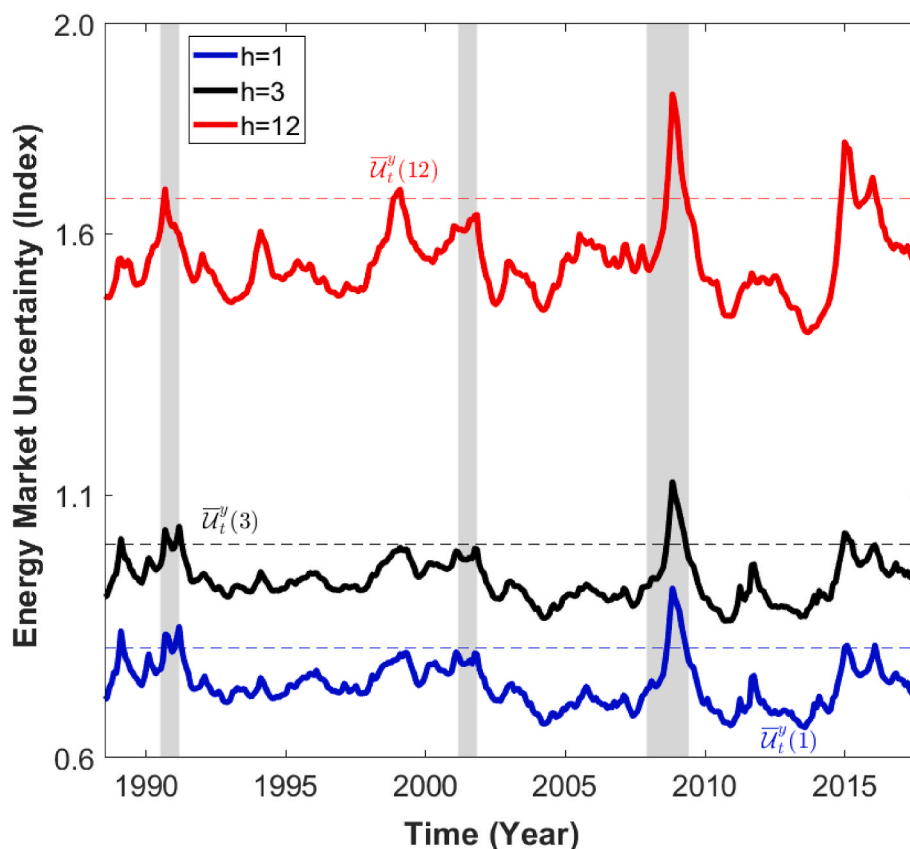


Fig. 1. Aggregate energy market uncertainty.

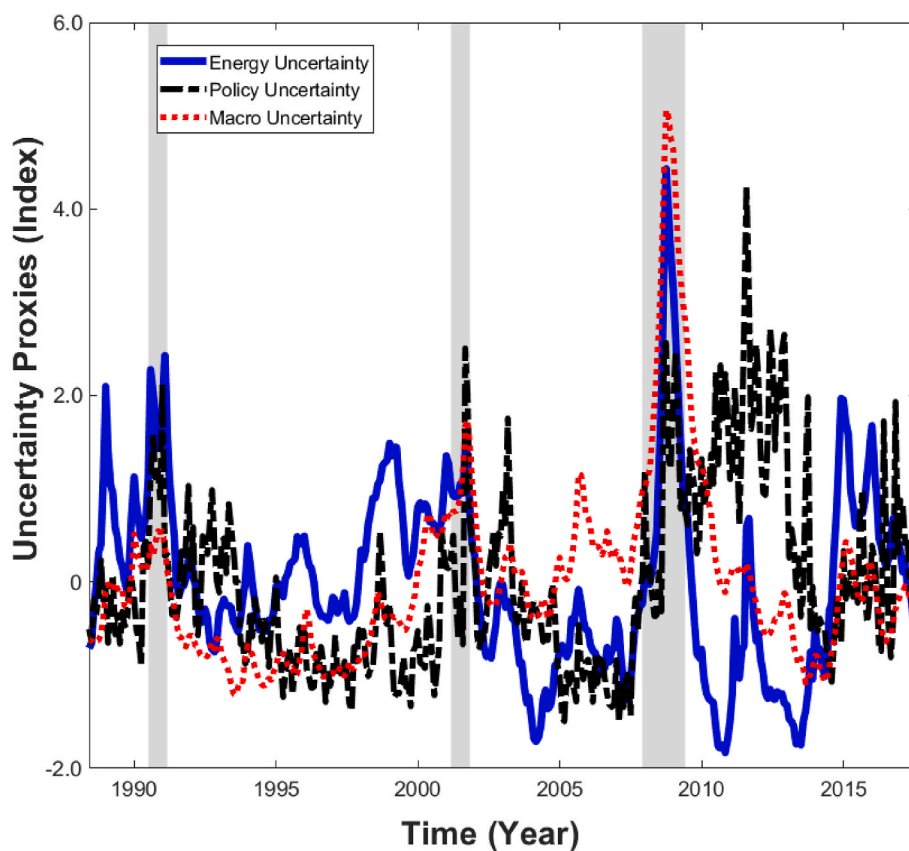


Fig. 2. Energy market, policy, and macroeconomic uncertainty.

Table 2
Correlation between energy, policy and macroeconomic uncertainty indicators.

	Energy Uncertainty	EPU	JLN Uncertainty
Energy Uncertainty	1		
EPU	0.06	1	
JLN Uncertainty	0.49	0.33	1

Notes: This table reports the correlation between 3 uncertainty indicators: 1) our constructed energy market uncertainty index, 2) Baker et al. (2016)'s EPU, and 3) Jurado et al. (2015)'s JLN.

components, especially for the energy market. These are crucial for decision making processes on energy-related investment and consumption, and energy policy making.

To account for heterogeneity in energy market uncertainty, we

further decompose the aggregate energy uncertainty index into seven sectoral energy market uncertainties: energy price uncertainty, energy demand uncertainty, alternative energy demand uncertainty, energy supply uncertainty, inventory uncertainty, macroeconomic uncertainty and financial uncertainty. We generate sectoral energy uncertainty indices by classifying variables into corresponding sectors and then aggregating them within each sector. Fig. 3 shows important differences among these sources which underscores heterogeneity in global energy uncertainty. For example, we find a negative relationship between energy price uncertainty and alternative demand uncertainty, which suggests that a high level of energy price surprises is linked with a low level of uncertainty raised from alternative energy demand (e.g., biomass, nuclear electric power, hydroelectric power, geothermal energy and wind). The pattern of macroeconomic uncertainty generated from the

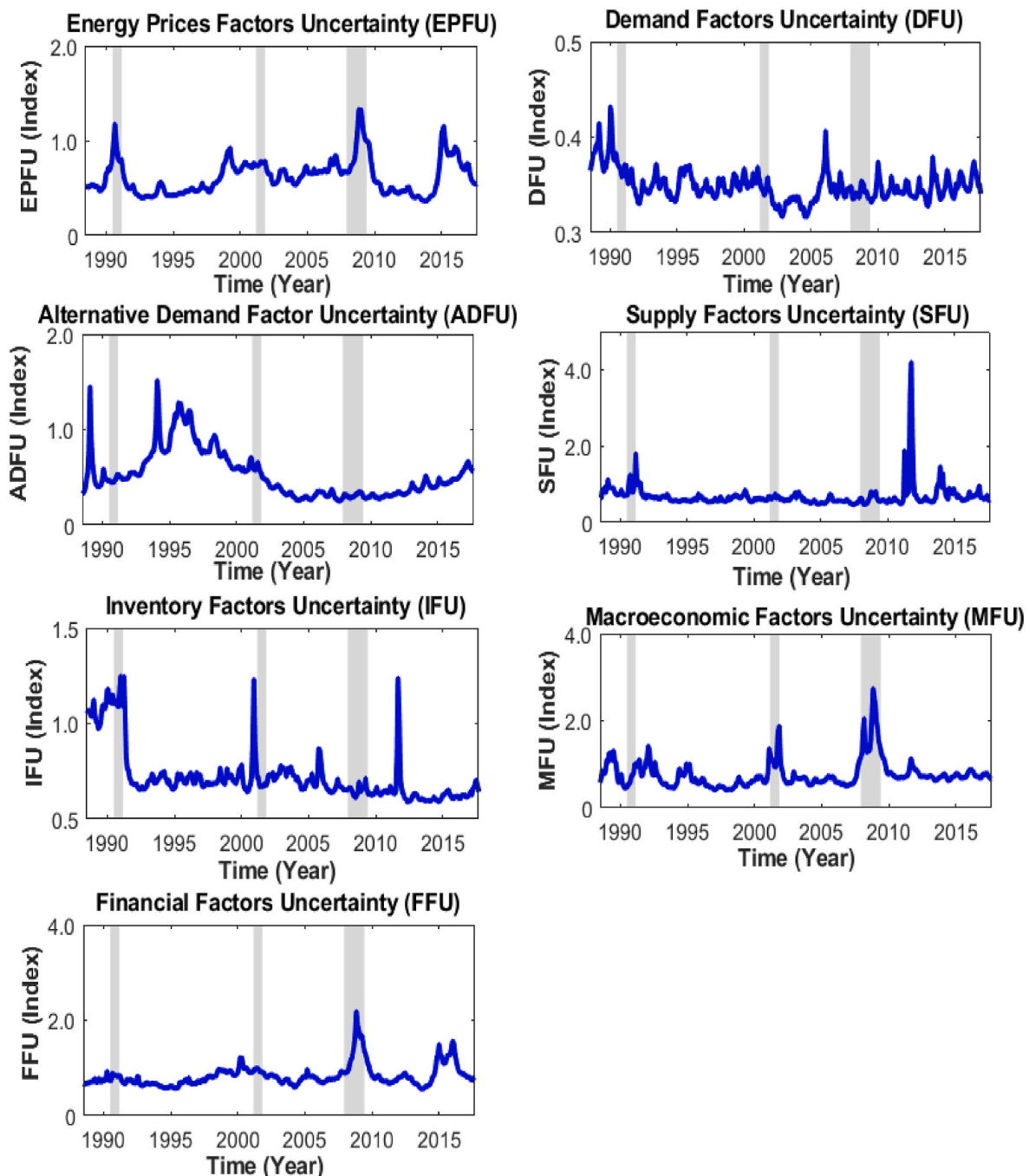


Fig. 3. Decomposition of energy uncertainty index.

aggregate energy uncertainty index is similar to that in [Jurado et al. \(2015\)](#), although we only include 15 macroeconomic variables in the uncertainty generating process. In addition, energy firms' financial uncertainty captures surprises from the finance market, such as the peaks which occurred during the stock market crash at the end of 1987, the Asian crisis in 1997, the Dot.com bubble in 2001, the Gulf War in 2003, and, of course the Great Recession in 2007. Given the heterogeneous uncertainty across different sectors, it is worth exploring the impact on the energy market.

5.2. The response of oil prices to energy market uncertainty

Figs. 4–6 show the impulse responses of the price of oil to global supply, aggregate demand, and energy market uncertainty shocks. The results are presented in a 20-months response horizon using our B-SVAR models. The solid line represents the posterior median, while the 16th and 84th percentiles of the posterior distribution are drew by two dashed lines.

Firstly, using our proposed 1-month ahead aggregate energy market uncertainty indicator, we find that an unexpected surge in oil supply depresses the price of oil substantially after 2 months as the zero axis is within the 68 % posterior credible interval - see [Fig. 4](#). In contrast, the demand shock caused by an unanticipated surge in worldwide demand for all industrial commodities results in a noticeable growth in oil prices. The response peaks after 2 months and evens out shortly afterwards. Our

findings are similar to previous literature, who also highlight the key role played by macroeconomic fundamentals in shaping oil price fluctuations (e.g., [Byrne et al., 2019](#)).

The last graph in [Fig. 4](#) shows that a positive shock from uncertainty on future energy market environments causes an immediate decrease in the real price of oil. The results are aligned with the literature which also shows oil prices respond negatively to uncertainty proxies (e.g., [Aloui et al., 2016](#); and [Joëts et al., 2017](#)). This is reasonable as a high degree of uncertainty in energy markets is likely to affect both the demand and supply on oil and, subsequently, the price of oil. For example, consumers may curtail their consumption in energy products and raise their precautionary savings with respect to higher uncertainty (e.g., [Kilian, 2008](#); [Edelstein and Kilian, 2009](#)); oil producers may postpone their investment in exploration and development, leaving oil reserves below the ground until further information becomes available ([Van Robays, 2016](#)).

Next, we compare and contrast the response of oil prices to our proposed energy market uncertainty indicator with EPU and JLN. As can be seen from the first and second panels of [Figs. 5 and 6](#), oil price responses to both demand and supply shocks are like our main results in [Fig. 4](#). However, our proposed energy market uncertainty indicator has a more persistent effect on the real price of oil than economic policy uncertainty proxy. This maybe because our proposed energy market uncertainty indicator captures a common variation in uncertainty across a large set of energy related variables, while EPU captures the timing and content of policy changes.

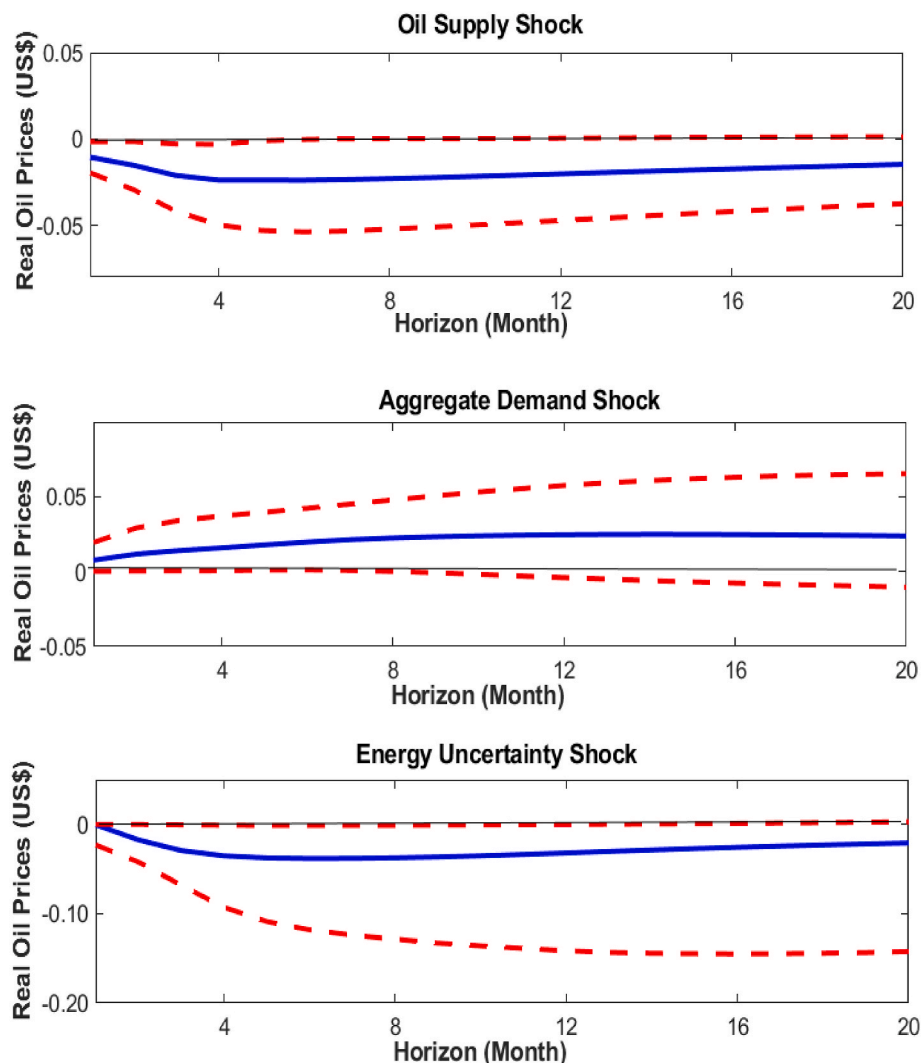


Fig. 4. Responses of Real Price of oil to Supply, Demand and Energy Market Uncertainty Shocks.

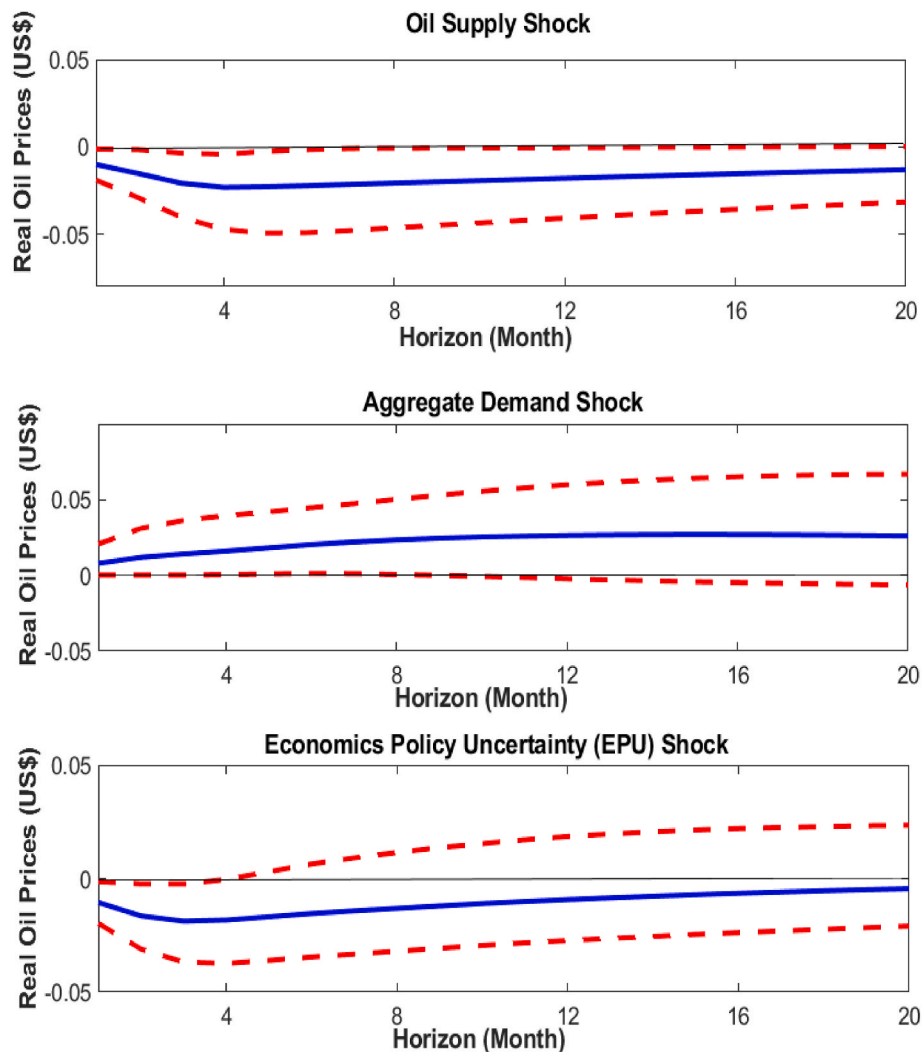


Fig. 5. Responses of Real Price of oil to Supply, Demand and.

Another important question is the extent to which the variation in oil price can be attributed to supply, demand, uncertainty, and other shocks. We answer this by estimating the forecast error variance decomposition (FEVD) of oil prices. Table 3 reports each shock's contribution to the total variation in oil prices. To be more specific, Part A (B and C, respectively) presents the FEVD of the real oil price, consisting of supply, demand, and energy market uncertainty shocks (i.e., EPU and JLN, respectively). We find that the contributions from supply, demand, and uncertainty shocks on the real price of oil are minor in the short-term. Nevertheless, the effects of supply, demand, and energy market uncertainty shocks in the global energy market surges remarkably as the horizon increases. To be more specific, energy market uncertainty has an important effect on the oil market, in that 30.57 % of the variations in the real price of oil are driven by global energy market uncertainty after 12 months. On the other hand, when we proxy uncertainty using the EPU indicator, it explains less than 9 % of the variation of oil prices in the long-run - see Part B of Table 3. Finally, in terms of the model using JLN macroeconomic uncertainty, we find that JLN shocks explain 24.89 % of the variability of oil price fluctuations 12-months following the shock.

In sum, the results further confirm that our proposed energy market uncertainty indicator is important in explaining oil price movements.

5.3. Factor-specific uncertainty effects

To account for heterogeneity in the source of uncertainty, we replace the aggregate energy market uncertainty in our Bayesian SVAR model with seven sectoral factors comprising energy price uncertainty, energy demand uncertainty, alternative energy demand uncertainty, energy supply uncertainty, inventory uncertainty, macroeconomic uncertainty, and financial uncertainty. The impulse responses of oil prices to the above-mentioned seven factors are shown in Fig. 7.

Our results highlight that the oil price responds differently to these uncertainty shocks. Firstly, energy demand shocks, energy supply shocks and inventory shocks have negligible effects on the real price of oil. Secondly, our results reveal that macroeconomic, financial market, and energy price uncertainty have a strong and immediate negative impact on oil prices. The responses reach their peak after five months. This is reasonable as global macroeconomic conditions can have a significant impact on demand and oil prices (e.g., Kilian, 2009); for example, the 2007 Global Financial Crisis caused market volatility to rise to levels rarely seen since the Wall Street Crash. Hence, large fluctuations in macroeconomic indicators can cause severe informational friction, leading to disorientation among market participants in terms of the state of the world economy and demand (Sockin and Xiong, 2015; Byrne et al., 2019). Furthermore, the fossil-fuel industry is considered to be highly vulnerable to extreme weather-related events. The cost of disruptions to its business operations and supply chains, and physical

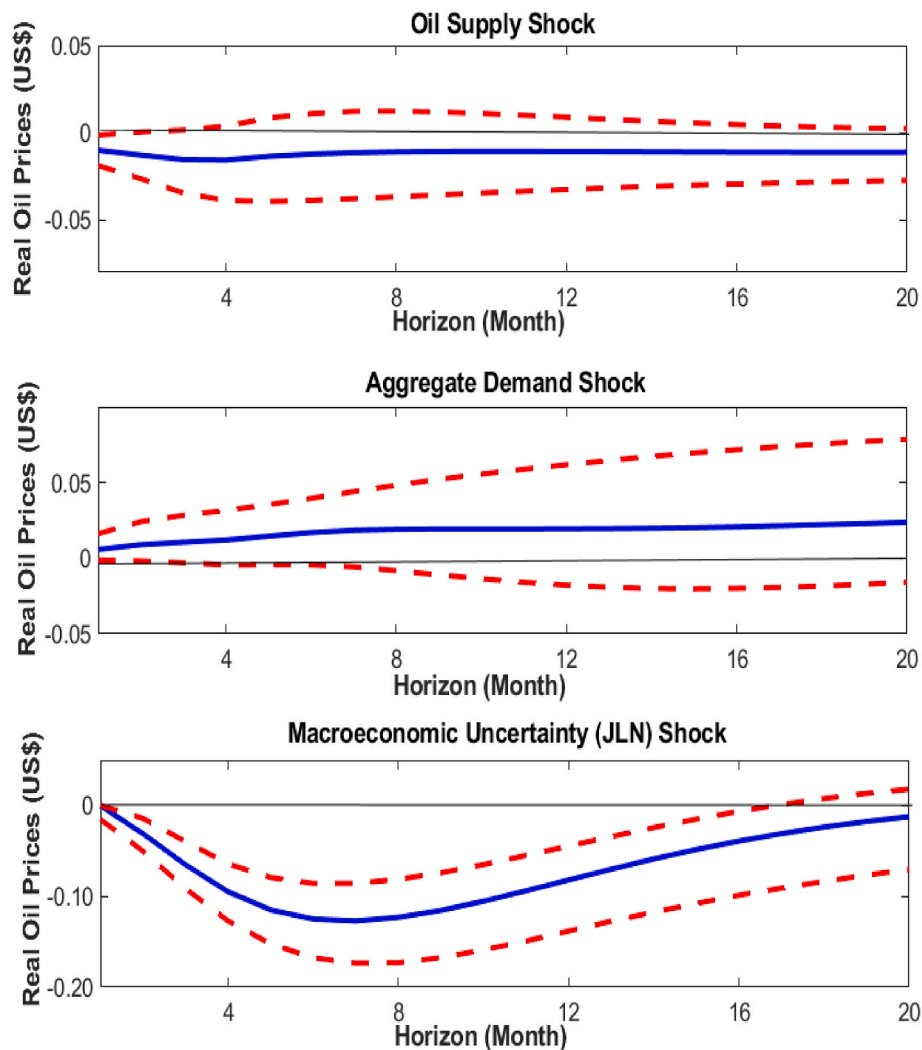


Fig. 6. Responses of Real Price of oil to Supply, Demand and.

damage to infrastructure and property caused by these events could be substantial. For instance, in 2020, five hurricanes caused serious disruption to oil production in the Federal Offshore Gulf of Mexico. Approximately 84 % of production was shut at the peak of the disruption due to crew evacuations (EIA, 2020). Such events can cause remarkable uncertainty about the financial performance of energy firms and negatively affect the real price of oil. In addition, we find that the alternative demand shocks caused by unanticipated surges in renewable resources cause a delayed but persistent diminishment in the real price of oil.

5.4. Implications for the Paris Agreement

The Paris Agreement is a legally binding international pact to tackle climate change. All member countries prepare, communicate, and maintain consecutive NDCs to be implemented to attain the objectives of the agreement (Article 4.2). However, the effectiveness of the agreement depends on whether the NDCs are to be fully implemented. If they are not, then the target of increasing the share of the renewable energy market share to 20 % cannot be achieved. Another policy uncertainty is the threat of the Trump Administration, on August 4, 2017, to withdraw from the agreement. President Joe Biden has renewed the US's commitment to tackle climate change, but the prospect of such a withdrawal from the agreement generated various degrees of uncertainty on the alternative energy markets. Therefore, it is worth examining the impact of various degrees of uncertainty on alternative energy demand

uncertainty on real oil prices.

Fig. 8 shows the impact on real oil price of a one standard deviation increase in the alternative energy demand uncertainty variable, depending on low ($\gamma = 0.2$), medium ($\gamma = 0.5$), and high ($\gamma = 0.8$) levels of alternative energy demand uncertainty. For other variables, γ is set at the medium distribution ($\gamma = 0.5$). It is clear from the top panel of Fig. 8 that when alternative energy demand uncertainty is relatively low ($\gamma = 0.2$), a shock on its uncertainty, arising from minor unexpected increases in alternative energy demand, causes a negative impact on real oil price of 0.014 after three months. The result in the middle panel indicates that when alternative energy demand uncertainty is moderate, an increase in uncertainty has a slight bigger impact on real oil price and results in a 0.02 decrease in price after 5 months. Finally, the last panel in Fig. 8 simulates very high ($\gamma = 0.8$) alternative energy demand uncertainty, and, in this scenario, the real price of oil decreases by 0.09. This is sensible as unexpected strong surges in alternative energy demand from renewable energy sources such as wind, solar and biomass could bring significant disruption to the traditional fossil-fuel industry (Kolosz et al., 2020). Therefore, it is critical to improve the use of green technologies to achieve carbon neutrality (e.g., Ahmad et al., 2021; Guo et al., 2021; Yue et al., 2021). Shahbaz et al. (2019), for example, conclude that investments in technological innovations and policies that discourage production of highly energy-intensive products are key to combat the carbon emissions. Mongo et al. (2021) also show significant evidence that environmental innovations reduce CO_2 emissions in the long run.

Table 3

Factor variance decomposition of forecasting errors of oil prices.

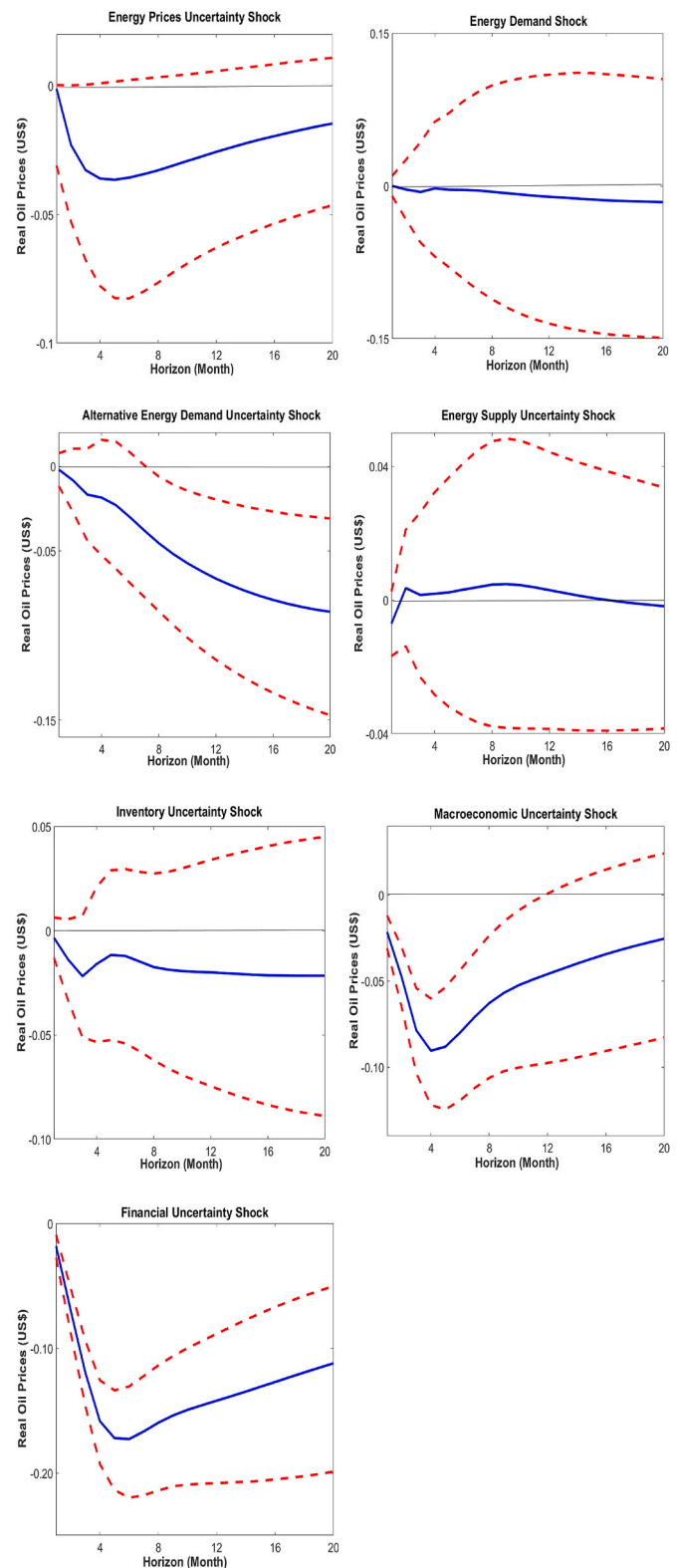
Part (A): Model Including Energy Market Uncertainty				
Horizon	Supply Shocks	Demand Shocks	Energy Market Uncertainty Shocks	Other Shocks
1	0.45 %	0.70 %	5.16 %	93.69 %
6	0.46 %	1.87 %	23.07 %	74.60 %
12	2.40 %	6.30 %	30.57 %	60.73 %
∞	4.55 %	22.68 %	41.27 %	31.50 %
Part (B): Model Including EPU				
Horizon	Supply Shocks	Demand Shocks	EPU Shocks	Other Shocks
1	0.32 %	1.58 %	0.25 %	97.84 %
6	0.21 %	5.17 %	0.82 %	93.80 %
12	1.43 %	10.99 %	2.17 %	85.41 %
∞	4.10 %	34.07 %	8.57 %	53.27 %
Part (C): Model Including JLN Macroeconomic Uncertainty				
Horizon	Supply Shocks	Demand Shocks	JLN Shocks	Other Shocks
1	0.07 %	1.89 %	0.82 %	97.22 %
6	0.09 %	3.18 %	16.80 %	79.93 %
12	0.76 %	9.78 %	24.89 %	64.57 %
∞	2.33 %	26.22 %	20.26 %	51.19 %

Notes: This table reports the extent each shock has contributed to explaining the real price of oil for 1-month, 6-months, 12-months ahead and infinity. To capture the dynamic impacts, we follow Kilian (2009) use a large length of two years.

Several robustness checks are carried on our main results. Firstly, we use different Cholesky ordering of variables and our results remain similar. Secondly, we test the robustness of our VAR models by employing different draw numbers, and use of different lag lengths (e.g., 6, 12 and 18). Results from these exercises do not alter our main findings. These results are available upon request.

6. Conclusion

Despite renewable energy targets and novel technological innovations (e.g., electric vehicles, low carbon fuels) playing critical roles in accelerating the global energy transition, oil remains an important source of energy in the short-to medium term. The real price of oil has important ramifications for the economic viability of alternative energy production which directly affects the oil-importing nations' energy securities. Our paper, therefore, builds on the existing literature identifying the determinants of oil prices by focusing on the role of uncertainty in the global energy market. In contrast to previous studies, we construct time-varying global energy market uncertainty indicators in a data-rich environment. Our uncertainty estimates exhibit notable differences from widely used proxies such as EPU and JLN. The results show that supply, demand, and uncertainty shocks have played important roles in explaining the real price of oil movements. Furthermore, by calculating the forecast error variance decomposition, we find that variations in the real price of oil can be attributed to supply, demand, uncertainty, and other shocks. Our proposed energy market uncertainty contributes 41.27 % of the variations in oil price in the long-run. In addition, we find the oil price can plunges by 0.09 due to unexpected high uncertainty for alternative energy sources demand.

**Fig. 7.** Response of oil price to sectoral factors.

In summary, our findings provide valuable insights from the point of view of risk assessment and investment decisions. By identifying the heterogeneity of sectoral responsiveness to changes in oil price, we can understand how the oil price responds to different types of uncertainty. For instance, while the financial market uncertainty of energy firms can cause an immediate sharp negative impact on the price of oil, inventory

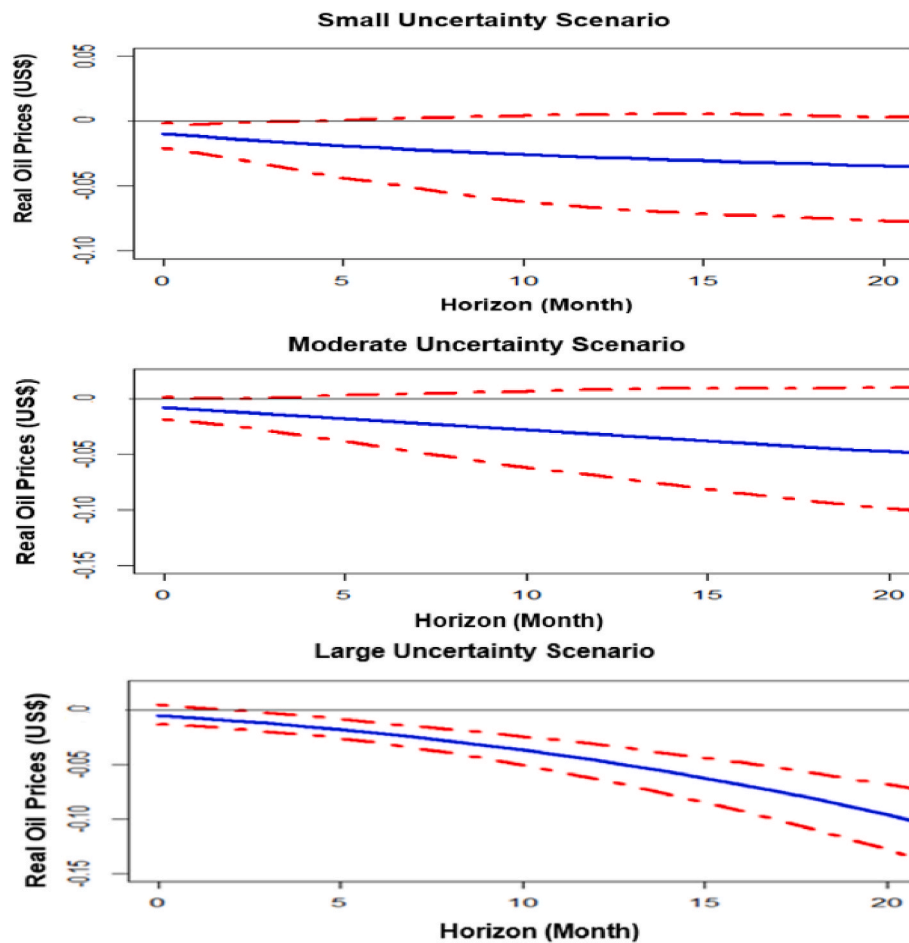


Fig. 8. Oil price responses to alternative energy demand uncertainty shocks.

uncertainty does not cause a response. A prudential risk assessment is necessary when the government is planning to invest in the Net Zero innovation portfolio because oil prices can be highly volatile in response to alternative energy sources, as our experiments indicate. One interesting future work is to test the predictive power of our proposed energy uncertainty indicator on the oil prices (Xu and Ouenniche, 2011; Ouenniche et al., 2014). Apart from quantitative analysis, one may utilize questionnaire-based surveys or a hybrid approach (e.g., interpretive structural modeling and analytic network process) to reach informed decisions regarding the implementation and effect of the Paris Agreement on the success of carbon neutrality targets.

Author statement

Bing Xu: Conceptualization; Project administration; Validation; Writing – original draft; Writing - reviewing and editing; **Rong Fu:** Methodology, Software; Formal analysis. **Chi Keung Marco Lau:** Methodology, Software, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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